Estimation of Range-Dependent Clutter Covariance by Configuration System Parameter Estimation

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SUMMARY & CONCLUSIONS

The range-dependent nature of the surface clutter power spectrum observed in monostatic or bistatic airborne radar systems results in a mismatch of the clutter covariance matrix (computed from a secondary set of range-cell data) relative to that of a possible target test cell, with attendant degradation of space-time adaptive processing (STAP) performance. In this paper, we develop a new method for predicting the test cell clutter covariance matrix by estimating the configuration system parameters that directly influence the clutter power spectrum. The method uses a multiple complex sinusoid model whose parameters are related to the configuration system parameters, which are then optimized to match the radar return pulse-train data in a least-squares sense. The estimated configuration parameters are then used to predict the clutter covariance matrix in the test cell, which is then used with traditional STAP methods. Computer simulation results are presented that demonstrate the significantly improved STAP performance obtained by the method developed here compared to the conventional method of using the sample covariance matrix estimated from secondary data.

1. *INTRODUCTION*

The detection of slow-moving (low-Doppler) ground targets from monostatic or bistatic airborne radars is difficult due to the high power level of surface clutter and the significant clutter Doppler spread. This spread tends to mask the return of a low-Doppler target. STAP techniques, using return pulse-train data obtained in the elements of an array antenna, exploit the angle-Doppler separation between target and ground clutter to provide enhanced detection of these types of targets. The application of various STAP methods requires the computation of a target-free clutter covariance matrix for each test range cell. This is typically done by straight averaging of the outer products of neighboring (secondary) range cell data snapshots. However, for bistatic radar systems and also for monostatic systems other than the specialized case of an ideal side-looking array, the clutter angle-Doppler characteristics vary with range. This causes the sample covariance matrix computed from secondary data set to be mismatched relative to the test cell. This results in a highly sub-optimum weight vector and degraded STAP performance in canceling clutter.

Various methods for compensating for the range variation of the clutter angle-Doppler ridges have been proposed in the literature including Doppler warping [1], higher order Doppler warping (HODW) [2], derivative based updating (DBU) [3], angle-Doppler compensation (ADC) [4], adaptive angle-Doppler compensation (A2DC) [5], and Registration-based approaches [6].

These methods attempt to align the peaks of the Doppler spectrum or the two-dimensional angle-Doppler spectrum of the secondary data with the test cell resulting in an approximate registration of the secondary clutter ridges with the test cell clutter ridge in angle and Doppler. However, these methods only accomplish partial compensation and, more importantly, implicitly assume that the test cell data is free of the desired target signal which contradicts the very purpose of doing the compensation.

The present work, on the other hand, attempts to estimate the underlying platform motion, antenna orientation and transmitter-receiver geometry parameters, i.e., the configuration system parameters, from the secondary data snapshots and use these estimates to predict the test cell covariance matrix. Examples of these configuration parameters include the transmitter and receiver velocity vectors (including the effects of unknown aircraft pitch and crab angles) and transmitter to receiver relative position vector. Nominal values of these parameters are available from GPS or inertial navigation system data and are used as initial estimates for the estimation technique developed here. The work reported here complements research previously reported in reference [6]. However, the estimation methodology proposed here is quite different. Furthermore, the test cell covariance matrix is explicitly estimated from the configuration system parameter estimates and used to improve STAP performance relative to the uncompensated case. The general methodology for estimating the configuration system parameters is based on using the full space-time data, i.e., element level-pulse train data, which will be presented at a future date. For present purposes, however, it is assumed that the receive array has already been beam formed and that just the pulse-train data at the beam level is available.

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE **01 MAY 2005**	2. REPORT TYPE **N/A**	3. DATES COVERED **-**

4. TITLE AND SUBTITLE **Estimation of Range-Dependent Clutter Covariance by Configuration System Parameter Estimation**	5a. CONTRACT NUMBER 5b. GRANT NUMBER 5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER 5e. TASK NUMBER 5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Air Force Research Lab/SNRT**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR'S ACRONYM(S) 11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release, distribution unlimited

13. SUPPLEMENTARY NOTES
See also ADM002017. Proceedings of the 2005 IEEE International Radar Conference Record Held in Arlington, Virginia on May 9-12, 2005. U.S. Government or Federal Purpose Rights License, The original document contains color images.

14. ABSTRACT

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**UU**	**6**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

2. *BISTATIC CLUTTER MODEL*

A brief description of the bistatic clutter model used in the simulation is given here. A rectangular array is used to transmit a coherent train consisting of N pulses in a given direction. The receive array is a uniformly spaced line array of M elements. Assuming a local flat earth, a constant bistatic range contour is an ellipse as shown in Figure 1. In the figure, the center reference point (CRP) denotes the point at which the transmit beam is directed. A bistatic range ring is the annulus between two ellipses whose width is inversely proportional to the transmit waveform bandwidth. The clutter range ring is divided into a large number, N_c, of small patches. The clutter return vector from a given bistatic range ring is the superposition of independent return vectors from these small patches, i.e., the clutter plus noise vector is given by

$$\boldsymbol{x}=\sum_{n=1}^{N_C} a_{C,n}\boldsymbol{d}_f\left(f_n\right)+\boldsymbol{n} \tag{1}$$

where $a_{c,n}$ and $\boldsymbol{d}_f(f_n)$ are the complex clutter amplitude and the Doppler steering vector for the n[th] clutter patch, respectively, f_n is the bistatic Doppler shift of the n[th] patch and $\boldsymbol{n}$ is the noise vector.

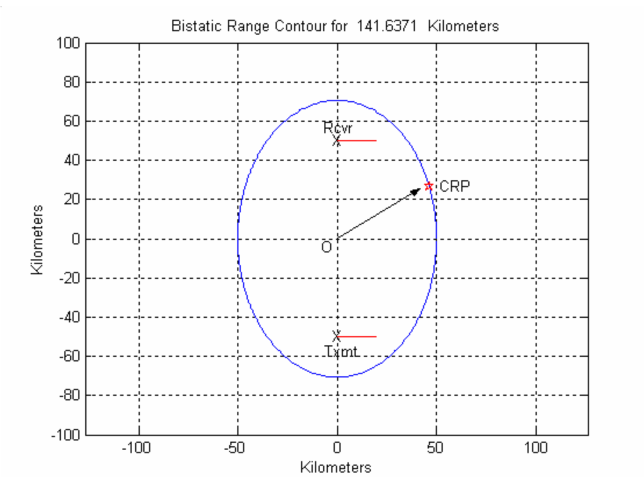

Figure 1. Bistatic range contour and system geometry

This clutter model is used to simulate the clutter temporal data in the test and secondary range cells and also the associated true and finite-data covariance matrices which are needed to evaluate performance.

The complex clutter amplitudes are statistically independent complex Gaussian random variables whose mean power for the n[th] patch is given by $E\left|a_{c,n}\right|^2=P_n$ where

$$P_n=\frac{P_T G_{T,n} G_{R,n}\lambda^2\sigma_{B,n}A_{C,n}}{(4\pi)^3 R_{T,n}^2 R_{R,n}^2}\ . \tag{2}$$

P_T is the transmit power, $G_{T,n}, G_{R,n}$ are the transmit and receive beam pattern power gains for the n[th] patch, respectively, λ is the wavelength, $\sigma_{B,n}$ is the clutter patch bistatic reflectivity and $A_{c,n}, R_{T,n}$ *and* $R_{R,n}$ are the area of the patch, the distance from the transmitter to the patch and the distance from the receiver to the patch, respectively. One model for the bistatic reflectivity is [7],

$$\sigma_{B,n}=\gamma\sqrt{sin(\theta_{T,n})sin(\theta_{R,n})}\quad , \tag{3}$$

where γ is the monostatic reflectivity, assumed constant for homogeneous terrain, and $\theta_{T,n}$ *and* $\theta_{R,n}$ are the transmitter and receiver grazing angles, respectively. The terms which are constant with respect to the position of the patch can be absorbed into a clutter power constant $K_P=\frac{P_T\lambda^2\gamma}{(4\pi)^3}$, which is regarded as unknown and is one of the configuration system parameters to be estimated.

3. *LEAST-SQUARES ESTIMATION OF CONFIGURATION SYSTEM PARAMETERS*

If the bistatic system parameters were perfectly known, the clutter space-time covariance matrix for any range cell could be predicted and the optimal weight vector for that range cell determined. However, in reality, the system and relative motion parameters are not known precisely. We propose to estimate these parameters using the return pulse-train data of the secondary range cells, and then predict the test cell covariance matrix. The parameters to be estimated are the receiver speed, heading (assuming level flight), the receiver position vector relative to the transmitter, the transmitter speed, the aircraft yaw and pitch angles, and clutter power level constant. The method developed here consists of modeling the clutter return pulse-train data for a given secondary range cell as being composed of a discrete number of complex sinusoids with unknown complex amplitudes and frequencies. These parameters of the multiple sinusoids are functionally related to the configuration system parameters which are then optimized to match the return pulse train data from all the secondary range cells in a least–squares sense. The complex amplitudes, which enter linearly in the model, are estimated by a closed-form linear least-squares estimation formula. Let $\boldsymbol{\alpha}$ denote the vector of unknown parameters. A model of *M* scatterers within the mainlobe is used whose Doppler steering vectors $\boldsymbol{d}_f(\boldsymbol{\alpha})$ are dependent on the parameter vector $\boldsymbol{\alpha}$. Typically, *M* = 2, 3 or 5. This then becomes a multiple complex sinusoid model. Let $\boldsymbol{x}$ denote the *N*-dimensional return pulse-train data vector for a particular range cell. Then

$$\boldsymbol{x}=\boldsymbol{D}(\alpha)\boldsymbol{a}+\boldsymbol{n} \tag{4}$$

where the *M* columns of the *N* by *M* matrix $\boldsymbol{D}(\boldsymbol{\alpha})$ are the Doppler steering vectors corresponding to the *M* scatterers in the model and are functions of $\boldsymbol{\alpha}$. $\boldsymbol{a}$ is the unknown complex amplitude vector. Minimizing the Euclidean norm

$$J(\boldsymbol{\alpha},\boldsymbol{a})=\left\|\boldsymbol{x}-\boldsymbol{D}(\boldsymbol{\alpha})\boldsymbol{a}\right\|^2, \tag{5}$$

with respect to $\boldsymbol{a}$ and $\boldsymbol{\alpha}$ can be accomplished by a two-step process. First, minimizing with respect to the amplitude vector $\boldsymbol{a}$ yields

$$\hat{\boldsymbol{a}} = \left[\boldsymbol{D}^H(\boldsymbol{\alpha})\boldsymbol{D}(\boldsymbol{\alpha})\right]^{-1}\boldsymbol{D}^H(\boldsymbol{\alpha})\boldsymbol{x},$$

where the superscript H denotes complex conjugate transpose.

Substitution of $\hat{\boldsymbol{a}}$ for $\boldsymbol{a}$ in (5) yields a function to be minimized solely with respect to $\boldsymbol{\alpha}$:

$$J_1(\boldsymbol{\alpha}) = \left\|\boldsymbol{x} - \boldsymbol{P}(\boldsymbol{\alpha})\boldsymbol{x}\right\|^2 \quad (6)$$

where

$$\boldsymbol{P}(\boldsymbol{\alpha}) = \boldsymbol{D}(\boldsymbol{\alpha})\left[\boldsymbol{D}^H(\boldsymbol{\alpha})\boldsymbol{D}(\boldsymbol{\alpha})\right]^{-1}\boldsymbol{D}^H(\boldsymbol{\alpha}) \quad ()$$

is the orthogonal projection operator that projects the data vector $\boldsymbol{x}$ onto the subspace spanned by the columns of $\boldsymbol{D}(\boldsymbol{\alpha})$ which are dependent on the unknown parameter vector $\boldsymbol{\alpha}$. Note that $\boldsymbol{P}^H = \boldsymbol{P}$ and $\boldsymbol{P}$ is idempotent i.e.; $\boldsymbol{P}^2 = \boldsymbol{P}$ and these properties have been used to obtain (6). Extension of (6) to estimating $\boldsymbol{\alpha}$ from multiple secondary range cells data is relatively straightforward and yields the criterion function to be minimized as

$$J_1(\boldsymbol{\alpha})(\alpha) = \sum_{k=1}^{K}\left\|\boldsymbol{x}_k - \boldsymbol{P}(\boldsymbol{\alpha})\boldsymbol{x}_k\right\|^2 \quad (7)$$

where the subscript k indexes range cells.

The minimization of (7) is a non-linear optimization problem. In the present work, the minimization of (7) has been accomplished using MATLAB's "fminsearch" function for optimization, which implements the Nelder-Mead simplex search algorithm. An alternative method, called the iterative re-linearization method based on a Taylor series expansion of the projection operator has also been developed and will be presented in the future. Since nominal values of the unknown parameters were available in the form of GPS or inertial navigation system data together with reasonable upper and lower bounds on these estimates, the MATLAB fminsearch method was augmented with a penalty function that effectively constrained the resulting solutions to lie within these bounds.

The power constant K_P is estimated as follows: The power in a given range cell data vector $\boldsymbol{x}$, $E\|\boldsymbol{x}\|^2$, where E denotes the expectation operator, is related to K_P via

$$\begin{aligned} E\|\boldsymbol{x}\|^2 &= N\sum_{n=1}^{N_C} P_n \\ &= NK_P\sum_{n=1}^{N_C}\frac{G_{T,n}G_{R,n}\sqrt{sin(\theta_{T,n})sin(\theta_{R,n})}A_{C,n}}{R_{T,n}^2 R_{R,n}^2} \end{aligned} \quad (8)$$

Since all the terms inside the summation sign in (8) are assumed known from the postulated clutter model, K_P can be solved for quite simply from (8) if $E\|\boldsymbol{x}\|^2$ were known. Since $E\|\boldsymbol{x}\|^2$ is not ,in general, known, we obtain an estimate of K_P by using $\|\boldsymbol{x}\|^2$ in place of $E\|\boldsymbol{x}\|^2$. For multiple secondary range cells, (8) is applied to each range cell data $\boldsymbol{x}_k$ and the resulting estimates of K_P are then averaged.

The test cell clutter covariance matrix is then estimated by using these estimated parameters in the model for clutter simulation described in Section 2. Note that the configuration system parameters have been estimated using the secondary range-cell data and excluding the test cell data, thus avoiding target signal cancellation. It is also to be noted that these parameters can be estimated using just one secondary range-cell data and a Toeplitz covariance matrix estimate of the test cell constructed (as opposed to the sample covariance matrix which requires the number of secondary range-cell data to be at least equal to N for full rank condition).

4. *COMPUTER SIMULATION RESULTS*

A MATLAB simulation has been developed to evaluate the performance of the proposed method. The objective is to determine and compare the signal-to-interference plus noise ratio (SINR) metric as a function of Doppler for the case where

1) the clutter covariance matrix was computed from the auxiliary data and applied to the test cell (uncompensated)
2) the configuration system parameters were estimated and used to generate the test cell covariance matrix and associated weight vector. For reference comparison, the performance of the optimal clairvoyant weight vector using the true test cell clutter covariance matrix was also evaluated.

For a given weight vector $\boldsymbol{w}$ computed using some estimate of the clutter covariance matrix $\hat{\boldsymbol{R}}$ via $\boldsymbol{w} = \hat{\boldsymbol{R}}^{-1}\boldsymbol{d}_f$, the SINR is given by

$$SINR = \frac{\left|\boldsymbol{w}^H\boldsymbol{d}_f\right|^2}{\boldsymbol{w}^H\boldsymbol{R}\boldsymbol{w}} = \frac{\left|\boldsymbol{d}_f^H\hat{\boldsymbol{R}}^{-1}\boldsymbol{d}_f\right|^2}{\boldsymbol{d}_f^H\hat{\boldsymbol{R}}^{-1}\boldsymbol{R}\hat{\boldsymbol{R}}^{-1}\boldsymbol{d}_f} \quad (9)$$

The parameters for the simulation were:

Frequency = 1.24GHz
Number of pulses = 32
PRF = 2000 Hz
Bandwidth = 4 MHz
Transmit array: 36 by 18 half wavelength spacing elements
Receive array: 16 elements uniformly spaced
Transmitter speed = 100 m/sec
Receiver speed =150 m/sec
Transmitter coordinates (0, -50, 4) km
Receiver coordinates (0, 50, 4) km.

We first show the results for only two unknown parameters, namely receiver speed and heading with assumed level flight motion, which required to be estimated. The bistatic range of the test cell was 141.65 km and one secondary range cell at a bistatic range of 145.2 km was used to estimate the parameters. The peak clutter-to-noise ratio (CNR) in the test cell was 60dB and 58.4dB in the secondary cell. It should be noted that the peak of the Doppler spectrum of the range cell is dependent on the dot product of the receiver velocity vector with the unit line of sight vector to the appropriate clutter mainlobe clutter patch and not individually on the speed and heading. This is approximately true in the vicinity of the entire mainlobe. Consequently, there is an ambiguity in the estimation of the receiver speed and heading separately. However, as will be shown below, this does not necessarily mean that the predicted test cell covariance matrix based on these parameters is significantly degraded from the true covariance matrix. Figures 2 and 3 show the least-squares error surface in the form of a 3-D plot and contour plot, respectively. It can be seen from these figures that the residual error surface is essentially flat in a certain direction which demonstrates this inherent ambiguity. The squared-error residual given by (6) was minimized using the MATLAB fminsearch function. The fminsearch algorithm was modified to include a severe penalty function if the resulting estimate during the function calls fell outside certain limits set based on a priori knowledge (such as GPS or inertial navigation data).

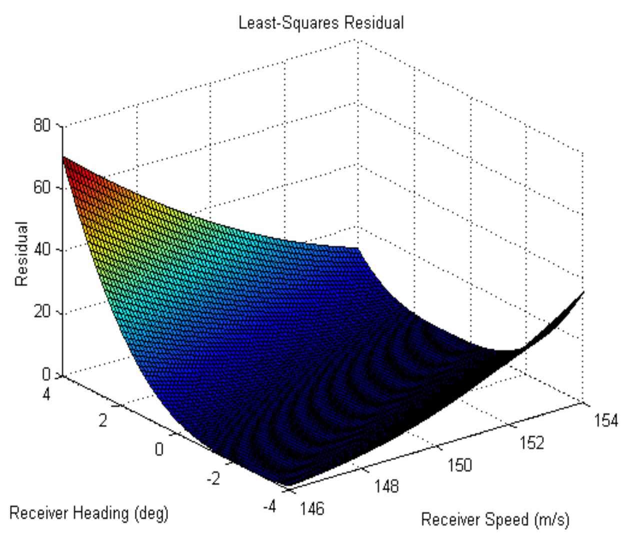

Figure 2. 3-D Least-Squares residual plot as a function of receiver speed and heading

This succeeded in constraining the solution to lie within these limits. As can be seen from Figure 3, the final estimate is not near the truth (150 m/sec speed and 0° heading), however its squared error residual is the lowest and is nearly on the constant error residual contour that passes through the true target point in speed and heading. This essentially means that the resulting estimated Doppler spectrum of the test cell and its associated covariance matrix is close to what would have been had the true parameters been used.

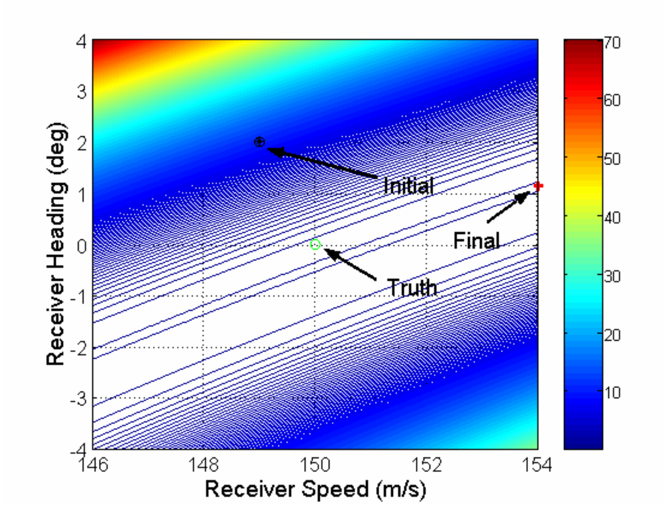

Figure 3. Contour Plot of the Least-Squares Residual

This is demonstrated in Figure 4 which shows the output SINR for the optimal clairvoyant case, the uncompensated case, and using the estimated parameters case. As can be seen, the SINR for the optimal clairvoyant case (using the true parameters) and the estimated parameters case are virtually identical and substantially better than the uncompensated case.

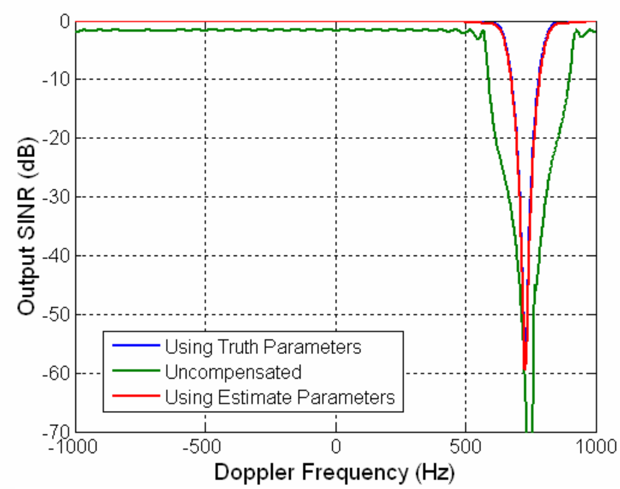

Figure 4. Output SINR, 2 estimated parameters

The simulation results using 7 unknown parameters, namely receiver speed and heading, 3-dimensional receiver position vector relative to transmitter, transmitter speed, and clutter return power constant K_p, are presented next. These parameters were optimized so as to minimize the squared-error residual given by (6). Figures 5 and 6 show the full-view and magnified view SINR for peak CNR of 30dB and one secondary range cell data used.

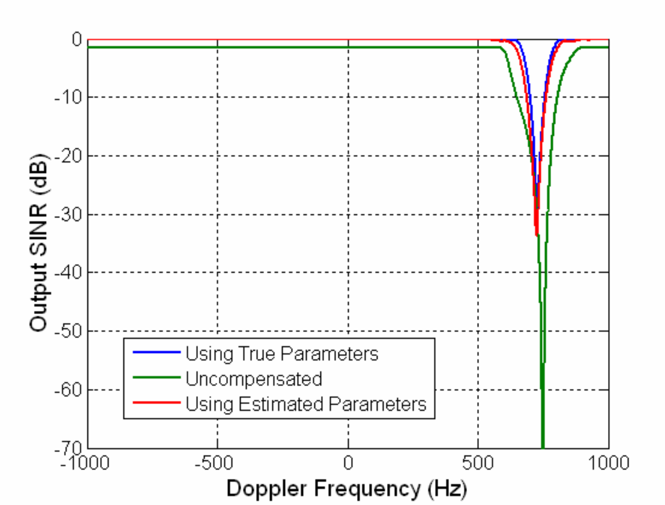

Figure 5. Output SINR, 7 estimated parameters, case 1

As can be seen, the SINR using the estimated parameters is very close to that using the true parameters and both are significantly better than the uncompensated case, particularly in the low target Doppler region in the vicinity of the notch in the SINR curves. The SINR of the uncompensated case tends to be displaced with respect to the optimal clairvoyant case, reflecting the fact that the secondary range cell Doppler spectrum is displaced and mismatched relative to the test cell.

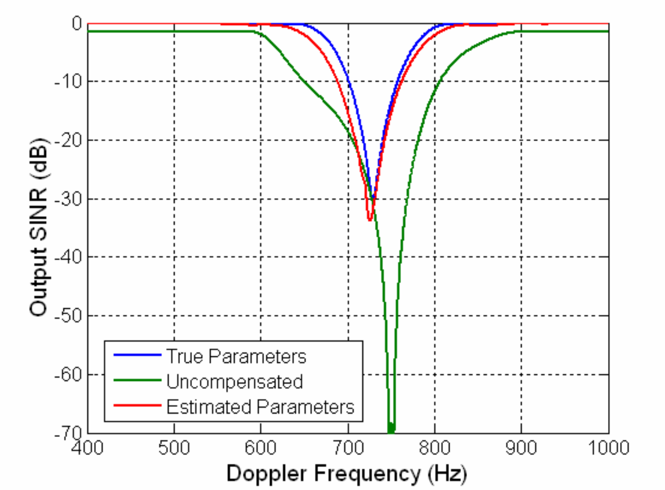

Figure 6. Magnified view of Figure 5, CNR = 30dB

Figures 7 and 8 show the corresponding results for peak CNR of 50dB.

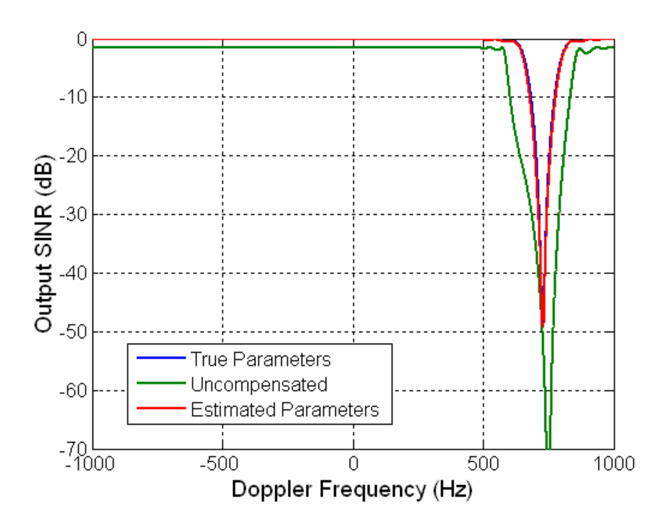

Figure 7. SINR's using 7 estimated parameters, CNR = 50dB

CONCLUSIONS

In this paper, we presented a new method for estimating the configuration system parameters using the return pulse train data from a secondary set of range cells. These estimated parameters were then used to predict the test cell clutter covariance matrix. Computer simulation results have shown that the resultant performance of adaptive Doppler filtering methods using these estimated parameters is substantially better than the uncompensated case and can be very close to the optimal clairvoyant case for moderately high clutter to noise ratios. More comprehensive simulation results, including parameter estimation using multiple range cells and extension to using full space-time data (array element-pulse train data) will shortly be available in an upcoming technical report.

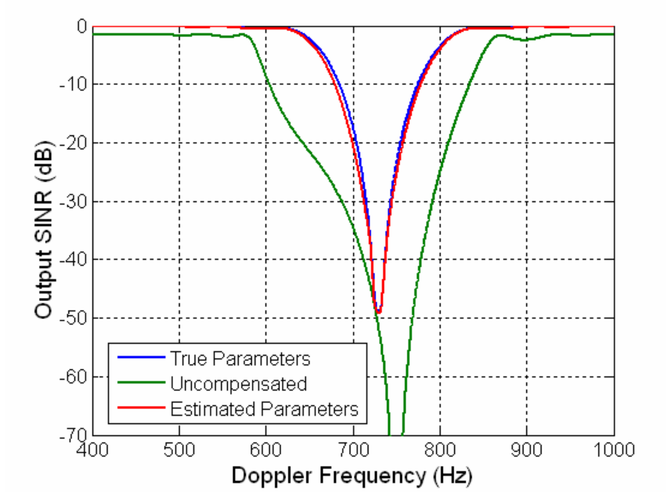

Figure8. Magnified view of Figure 7, CNR = 50dB

As can be seen, there is a further performance improvement of the estimated parameters case so that its SINR is almost identical to that of the case using the true parameters.

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BIOGRAPGIES

Amin G. Jaffer is a Sr. Principal Engineer at Raytheon Space and Airborne Systems, El Segundo, California. He obtained the MSEE degree from the University of Wisconsin, Madison and the PhD (EE) degree from Southern Methodist University, Dallas. He has over 34 years experience in the development and evaluation of techniques for detection, classification and tracking in radar and sonar systems including adaptive beamforming and space-time adaptive processing (STAP). Applications included TPQ-36 and 37 radars, ADCAP smart torpedo sonar system and SURTASS surveillance system. He has published 37 papers in adaptive processing, estimation theory and target tracking. He is also the holder of a U.S. patent on clutter tuning for bistatic radar systems. Dr. Jaffer has taught courses in electrical engineering at California State University, and courses on STAP at Raytheon Co. He was the recipient of Raytheon individual and team achievement awards in 1996, 1998, 2002, 2003 and 2004 for contributions to development of advanced signal processing methods for applications to radar and sonar systems.

Braham Himed is a senior research engineer with the United States air force research Laboratory, sensors directorate. He received his B.S. degree from Ecole Nationale Polytechnique of Algiers, Algeria in 1984, and his M.S. and Ph.D. degrees from Syracuse University, Syracuse, NY, in 1987 and 1990, respectively, all in Electrical Engineering. His research interests include detection, estimation, multichannel adaptive signal processing, time series analyses, array processing, space-time adaptive processing, hot clutter mitigation, and ground penetrating radar technology. Dr. Himed is a senior member of the IEEE and a member of the radar systems panel.

Phil Ho received the Bachelor of Science in Electrical Engineering from University of Colorado in 1983, Master of Science in EE from California Polytechnic University in 1991 and Engineer degree in EE from University of Southern California in 1999. Currently Phil is a Principal Engineer at Raytheon Space and Airborne System division in El Segundo, California. He is currently working in the area of space-time adaptive processing (STAP) and signal detection for Bistatic radar system. From 1984 to 2002, Phil had worked on tracker, digital signal processing for sonar, image processing for electrical-optical systems, control system design for infrared seeker. In 1998 Phil received individual award from Hughes for his work on the Closest Point of Approach Estimator.